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A spatial framework for *ex-ante* impact assessment of agricultural technologies

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ABSTRACT

Traditional agricultural research and extension relies on replicated field experiments, on-farm trials, and demonstration plots to evaluate and adapt agronomic technologies that aim to increase productivity, reduce risk, and protect the environment for a given biophysical and socio-economic context. To date, these efforts lack a generic and robust spatial framework for *ex-ante* assessment that: (i) provides strategic insight to guide decisions about the number and location of testing sites, (ii) define the target domain for scaling-out a given technology or technology package, and (iii) estimate potential impact from widespread adoption of the technology(ies) being evaluated. In this study, we developed a data-rich spatial framework to guide agricultural research and development (AR&D) prioritization and to perform *ex-ante* impact assessment. The framework uses "technology extrapolation domains", which delineate regions with similar climate and soil type combined with other biophysical and socio-economic factors that influence technology adoption. We provide proof of concept for the framework using a maize agronomy project in three sub-Saharan Africa countries (Ethiopia, Nigeria, and Tanzania) as a case study. We used maize area and rural population coverage as indicators to estimate potential project impact in each country. The project conducted 496 nutrient omission trials located at both on-farm and research station sites across these three countries. Reallocation of test sites towards domains with a larger proportion of national maize area could increase coverage of maize area by 79–134% and of rural population by 14–33% in Nigeria and Ethiopia. This study represents a first step in developing a generic, transparent, and scientifically robust framework to estimate *ex-ante* impact of AR&D programs that aim to increase food production and reduce poverty and hunger.

1. Introduction

Traditional agricultural research and development (AR&D) relies on field experiments, on-farm trials, and demonstrations to evaluate and promote adoption of agronomic technologies that aim to increase land productivity and reduce poverty, while improving resilience and reducing the environmental footprint for a given biophysical[1] and socio-economic context. To date, current efforts lack a generic spatial framework for *ex-ante* impact assessment that can help guide strategic decisions about the number and location of testing sites, pilot projects, and scaling out local results to larger spatial areas (Grassini et al., 2017; Rattalino Edreira et al., 2018). Without such a framework, agricultural

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[1] Soil properties and climate attributes that have greatest impact on crop growth and yields.

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research largely relies on other criteria, such as proximity to roads or experimental stations, and often with farmers who are not representative of the farming population at large (de Roo et al., 2017). Lack of quantitative tools to extrapolate results to larger areas diminishes the capacity to target the right set of technologies to the most receptive environments and farmers (Byerlee et al., 1988; Harrington and Tripp, 1984), which in turn would reduce return on investment (ROI) in AR&D.

Farmers' typically strive to reduce risk (van Oort et al., 2017) and maximize net profit by adopting cost-effective management practices that increase yield and/or input-use efficiency as influenced by the biophysical and socio-economic contexts (Sumberg, 2012). For rainfed crop production, response to a "package" of technologies (in terms of yield and/or input-use efficiency), should be predictable and of reasonably similar magnitude within a spatially defined region with similar weather (van Wart et al., 2013) and soil water holding capacity in the root zone (Rattalino Edreira et al., 2018). Such a unique combination of biophysical attributes is called a "technology extrapolation domain" (TED) (Rattalino Edreira et al., 2018). Use of TEDs can improve efficiency of on-farm field trials and analysis of producer survey data by increasing the crop area coverage from a fixed number of testing sites or surveyed regions (Mourtzinis et al., 2018; Rattalino Edreira et al., 2017, 2018). While we acknowledge other efforts to delineate domains for technology transfer, we note that most of previous efforts resulted into spatial frameworks that were too fine (e.g., Danvi et al., 2016; Muthoni et al., 2017; Singh et al., 1999) or too coarse (*e.g.*, FAO, 1978; Fischer et al., 2002; Padbury et al., 2002; Soil Survey Staff, 2006; Wood and Pardey, 1998) to be useful to inform and evaluate investments on AR&D in a generic and yet robust way.

Evaluation of the TED framework in the North Central US region indicated that biophysical variables used to delineate TEDs (root-zone soil water holding capacity and climate) accounted for much of the observed variation in crop yields because yield reductions from nutrient deficiencies and pest damage are relatively small and farmers have access to cost-effective technologies to avoid them (Grassini et al., 2014). In developing countries, soil properties other than water holding capacity may also represent major constraints (*e.g.*, soil acidity or salinity), as well as socio-economic factors governing access and affordability of required technologies to alleviate them. Hence, TEDs may require additional specification of such factors to assess the likelihood of technology adoption, especially in regions where farmers have limited access to markets, inputs, and extension education, and to quantify the impact of programs that have an explicit focus on reducing poverty and malnourishment (Croppenstedt et al., 2003; Nkonya et al., 1997; Thirtle et al., 2003; https://ccafs.cgiar.org; https://www.usaid.gov). In other words, a robust spatial framework should be flexible enough to integrate both biophysical and socio-economic factors to have broad applicability across a wide range of agricultural systems and environments, and be useful for *ex-ante* impact assessment.[2]

The objective of this study is to present a generic spatial framework that combines biophysical and socio-economic attributes for *ex-ante* impact assessment of AR&D programs. Such a framework has the potential to improve the efficiency and effectiveness of AR&D investments through identification of highest impact in terms of increasing regional crop production and lowering risks and, by doing so, contribute to reducing poverty and malnourishment. We highlight the principles that underpin development of the framework and provide proof of concept using a nutrient-response trial program in sub-Saharan Africa as a case study. While we focus on the impact of technologies to close existing yield gaps, the framework can also be used in programs that aim to improve input-use efficiency and increase resilience of agricultural systems.

2. Materials and methods

2.1. Framework development

Yield potential is the yield of a well-adapted cultivar when grown without nutrient limitations and kept free of biotic constraints such as weeds, diseases, and insect pests (Evans, 1993). Hence, in absence of these limiting and reducing factors, yield is determined by solar radiation, temperature, and, in the case of rainfed crops, precipitation and soil properties influencing crop water balance (van Ittersum et al., 2013). The yield gap is the difference between yield potential and average farmer yield. It provides a useful indicator to discern changes in crop productivity due to technology adoption as it accounts for spatial and temporal variation in the factors that drive yield potential (Lobell et al., 2009). The yield gap can be interpreted relative to their proximate and ultimate causes (Sadras et al., 2016). For example, insufficient nitrogen (N) supply is a typical proximate cause of yield gaps, but the underpinning causes may be related to socio-economic factors such as availability and cost of fertilizer and access to technical information on how to use it (Gurara and Larson, 2013; van Dijk et al., 2017). Hence, probability of narrowing the yield gap is greater when a technology[3] to remove the proximate cause of the yield gap exists and the socio-economic environment fosters adoption.

We developed a generic framework (Fig. 1) that builds on the biophysical TED framework developed for the Global Yield Gap Atlas (Rattalino Edreira et al., 2018; http://www.yieldgap.org/web/guest/czted). Briefly, the TED framework delineates regions with similar climate and soil water holding capacity (see description below). Here, we bring other factors into the TED framework, recognizing the importance of both biophysical and socio-economic conditions in driving technology adoption and impact in agricultural systems. The framework allows *ex-ante* impact assessment using parameters that are relevant to the goals of a given AR&D program, potentially serving also as a tool for monitoring and *ex-post* impact assessment (Grassini et al., 2017).

The proposed framework consists of seven steps (Fig. 1):

Step (1)

Selection of target geographic area (*e.g.* region, country, administrative unit, agro-ecological zone, etc.), cropping system, and technology (or suites of technologies) as identified *a priori* by the AR&D program and the entities funding the research. Typical funders include government agencies within a country, development agencies in developed countries, private sector companies, non-governmental organizations (*e.g.* environmental advocacy groups), and large charitable foundations.

Step (2). Mapping of TEDs within the target region

TEDs are delineated based on four key biophysical attributes with greatest influence on yield potential and yield stability. Three of these attributes are climate-related parameters that delineate climate zones (van Wart et al., 2013): (i) annual total growing degree-days (sum of daily temperature after subtracting a base temperature), which, in large part, determines the length of crop growing season, (ii) aridity index, calculated as the ratio between annual precipitation and potential evapotranspiration, which reflects the degree of water limitation in rainfed cropping systems, and (iii) annual temperature seasonality, which differentiates between temperate and tropical climates. A fourth attribute, plant-available water holding capacity in the rootable soil depth, determines the capacity of a soil to supply water to support crop growth during rain-free periods.[4] Each TED corresponds to a unique

[2] Procedure to evaluate the potential impact on system performance (*e.g.* yield, income, soil erosion, etc.) from widespread adoption of a new technology.

[3] Application of knowledge/set of techniques for practical purposes.

[4] Two of the TED attributes are not as relevant for irrigated agriculture such

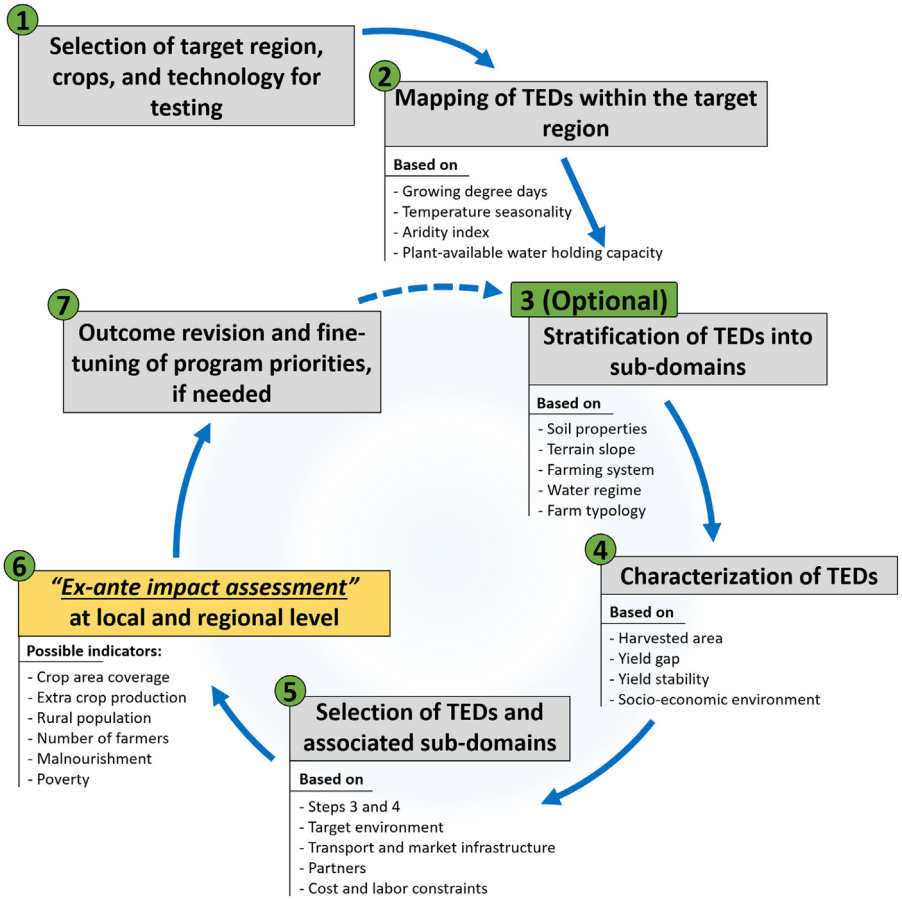

Fig. 1. A generic framework for *ex-ante* impact assessment in rainfed crop agriculture. Sequential steps are numbered from one to seven. A detailed description of each step is provided in the main text. TED: technology extrapolation domain.

combination of these four spatial variables. For example, the TED framework developed for sub-Saharan Africa (SSA) is shown in Fig. 2. A detailed description of the TED framework development and validation is reported elsewhere (Rattalino Edreira et al., 2018; http://www.yieldgap.org/web/guest/cz-ted).

Step (3). Stratification of TEDs into sub-domains

Technology adoption and impact can be influenced by other factors besides those used to delineate the TEDs such as soil chemical properties, terrain slope, farming system, farm typology, and water regime. For example, adoption of a technology can vary between large and smallholder farms located within the same TED (Lopez-Ridaura et al., 2018); in this case, it would be desirable to have two sub-domains to account for the contrasting farm typology. Likewise, the impact of a technology on yield can differ markedly across soils with large differences in pH within the same TED, or within a single farm (Chikowo et al., 2014; Tittonell et al., 2005) in a region where soil amendments (such as lime) are not available to modify pH. Hence, if there are other biophysical and socio-economic factors relevant to the program objectives, creation of "sub-domains" within TEDs may be needed to account for their influence on technology adoption and impact. The number of sub-domains, however, should be limited to the most important factors affecting performance of the crop production system; if too many

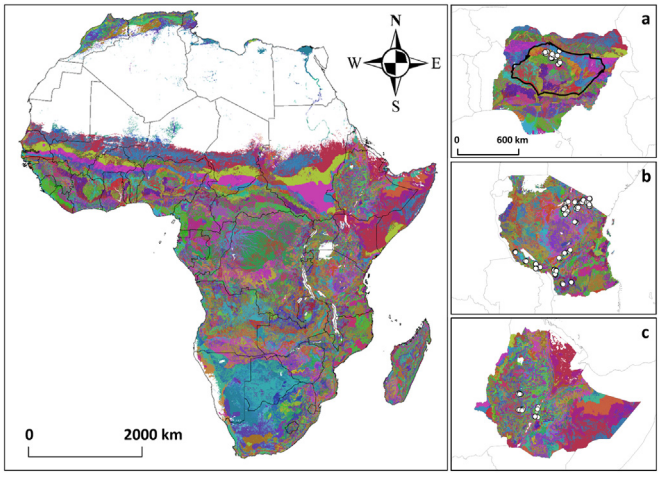

Fig. 2. Technology extrapolation domains (TEDs) in Africa based on both the climate zone scheme developed by van Wart et al. (2013) and spatial data on plant-available soil water holding capacity in the root zone from the Africa Soil Information Service (Leenaars et al., 2018; AfSIS). Each color represents a unique TED, whereas land area in white corresponds to climate zones where major food crops are not grown (van Wart et al., 2013). Current trial locations of the Taking Maize Agronomy to Scale in Africa (TAMASA) program are indicated with white dots in Nigeria (a), Tanzania (b), and Ethiopia (c). The program focused exclusively on the savanna agro-ecological zone in Nigeria (borders are shown in black). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(*footnote continued*)
that the framework can be simplified to exclude soil water holding capacity and aridity index to evaluate irrigated systems. Hence, the same stepwise process shown in Fig. 1 could be used with the simplified TED framework for irrigated agriculture.

factors are included, representing the range of possible TEDs and sub-domains becomes unmanageable. These sub-domains may not be spatially explicit within the TEDs as spatial information usually does not account for micro heterogeneity at field/local level.

Once the target sub-domains are identified, the next question is how many sites are needed per sub-domain to adequately vet the technology (ies) being evaluated. More than one site per sub-domain might be desirable for TEDs with large extent and to account for unintended failures in the implementation of the program (*e.g.*, trials lost due to hail or livestock) and for variation in unaccounted factors. Likewise, number of sites per domain may need further adjustment based on the uncertainty associated with underpinning climate and soil data used to develop TEDs and sub-domains (Grassini et al., 2015). As a rule, the more reliable the underpinning data are, the smaller the number of required sites. Expert opinion, complemented with analysis of legacy data, if available, should also help to decide the number of sites per sub-domain.

Step (4). Characterization of TEDs

The framework is flexible on this step, as the characterization of TEDs will be based on the program goals, such as poverty reduction, improved nutrition or soil conservation. Data layers that might be considered as overlays to the TED framework include crop area, yield gaps, inter-annual yield variation (*i.e.*, a proxy to climate risk) and demographic or socio-economic factors such as rural population, poverty, nutritional status, farm size, production objectives, access to markets, etc.

Step (5). Selection of TEDs and associated sub-domains

Once the TEDs within the target area have been characterized based on key attributes from step 4, it is possible to rank them from the most to the least relevant according to the program goals. In many cases, the number of selected TEDs would be determined by the required number of sites per sub-domain (step 3) and funding resources available to support the evaluation. Further refinement may be needed based upon partner availability and logistics; for example, it may be difficult (if not impossible) to have sites in extremely remote areas. Likewise, if it is known that the technology is more likely to work best in specific environments (*e.g.*, sandy soils in cool environments, or environments with reliable rainfall) and socio-economic factors that favor adoption (*e.g.*, access to market), specific regions within a TED zone can be identified to meet specific criteria. After step (5), the outcome is a list of TEDs (and associated sub-domains) explicitly selected based on priorities of the research program, conditions under which the technology (ies) under evaluation are most likely to perform well and be adoptable, and logistical constraints governing where the trial sites can be established.

Step (6). Ex-ante impact assessment at local and regional level

Indicators to evaluate potential impact of a technology may range from simple calculations of crop area, rural population, and number of farmers that would be impacted by the program to more specific metrics such as the extra crop production that would result from widespread adoption of the technologies being evaluated, or reduction in poverty and malnourishment to name a few. The framework allows *ex-ante* impact assessment across spatial scales from districts to provinces, states and countries through aggregation procedures developed by the GYGA project for upscaling estimates of yield gaps (van Bussel et al., 2015). Combining estimates of impact on yield with economic analysis of cost and benefits from technology adoption can provide an objective measure of ROI as well within the same spatial structure.

Step (7) Outcome revision and fine-tuning

Based upon the impact calculated in step (6), it may be necessary to re-iterate from step (3) to fine-tune site selection and explore different scenarios. Once the program is established, the framework can be used as a tool to monitor impact over time using the same set of indicators used for the *ex-ante* evaluation.

2.2. Case study

Hundreds of millions of dollars are invested every year on AR&D programs in SSA by governments, international donors, and the private sector (Kassam, 2007; Piesse and Thirtle, 2010; Pardey et al., 2013). We used the spatial framework to evaluate the potential impact of an ongoing maize agronomy project in SSA as a case study. We used maize as a case study because: (i) maize accounts for as much as one third of total caloric intake in some SSA countries (Naylor et al., 2007), (ii) maize area in Africa is increasing rapidly (from 28 to 41 Mha in the last decade) (FAO, 2018), and (iii) there is large potential to increase maize yields through better agronomic management (van Ittersum et al., 2016). The project "Taking Maize Agronomy to Scale in Africa" (TAMASA, http://www.tamasa.cimmyt.org) seeks to improve nutrient use-efficiency, productivity, and profitability of smallholder maize farmers in Ethiopia, Nigeria, and Tanzania through development and use of nutrient management decision support tools. The program conducted 496 on-farm nutrient omission trials to assess nutrient deficiencies and responses, and to parameterize a decision-support tool for fertilizer application (Nutrient Expert; http://software.ipni.net/article/nutrient-expert) (Fig. 2). In 2015, a total of 78, 95, and 323 trials were conducted in Ethiopia, Nigeria, and Tanzania, respectively. In each country, TAMASA selected sites based on geographic or administrative areas where suitable partners were available, size of maize production area, population density ($> 25\,km^{-2}$), and access to market quantified as distance to market (travel time < 4 h). Sites were selected based on a stratified sampling of 10×10 km cells, allocating 10–15 replicated trials within these areas, following well established protocols (Kihara et al., 2016; Njoroge et al., 2017). Field sites were selected to represent a composite index of soil organic matter content (SOC), pH, soil texture, and cation exchange capacity (CEC). In the case of Nigeria, the program explicitly focused on the northern Nigerian savanna agro-ecological zone and selection of the area of interest was constrained to this region (Shehu et al., 2018). Evaluation of TAMASA trials within the TED framework found that these trials were located in TEDs that accounted for 22% (Ethiopia) and 75% (Tanzania) of national maize area. In the case of Nigeria, trials were located in TEDs that account for 74% of the maize area located within the target agro-ecological zone and 31% of national maize area.

Current TAMASA's trial site allocation was compared with three alternative scenarios derived from application of the assessment framework of Fig. 1 with the goal of achieving greatest impact in terms of maize area and rural population coverage without increasing number of sites or, alternatively, achieving the same level of impact with fewer sites. Following step (2) in our framework, we first disaggregated each country into TEDs (Fig. 2). Given that one goal of the TAMASA project is to evaluate yield response to nutrients and design fertilization recommendations to reduce the yield gap, we created sub-domains within TEDs based on two additional soil factors (pH and organic carbon content [SOC]) following Step 3 of Fig. 1. Among soil fertility factors, soil pH and organic matter content are known to have a large influence on yield response to addition of fertilizer nutrients (*e.g.*, Kihara et al., 2016; Wortmann et al., 2017; Shehu et al., 2018); hence, it is relevant to consider them when selecting experimental sites. We used gridded estimates of soil properties (250×250 m spatial resolution) for different soil depth intervals (0–5, 5–15, and 15–30 cm; http://www.isric.org) and calculated a weighted average for the entire (0–30 cm) topsoil (Fig. 3). Four different soil classes were created (Step 3, Fig. 1) combining two pH categories (< 5.7 and > 5.7) and two categories of SOC (< 12.5 and $> 12.5\,g\,kg^{-1}$) (Fig. 3). Thresholds were based on observed ranges for these two variables and their influence on crop growth (Hengl et al., 2015; Kihara et al., 2016; Leenaars et al., 2018; Shehu et al., 2018; Wortmann et al., 2017). These soil classes were

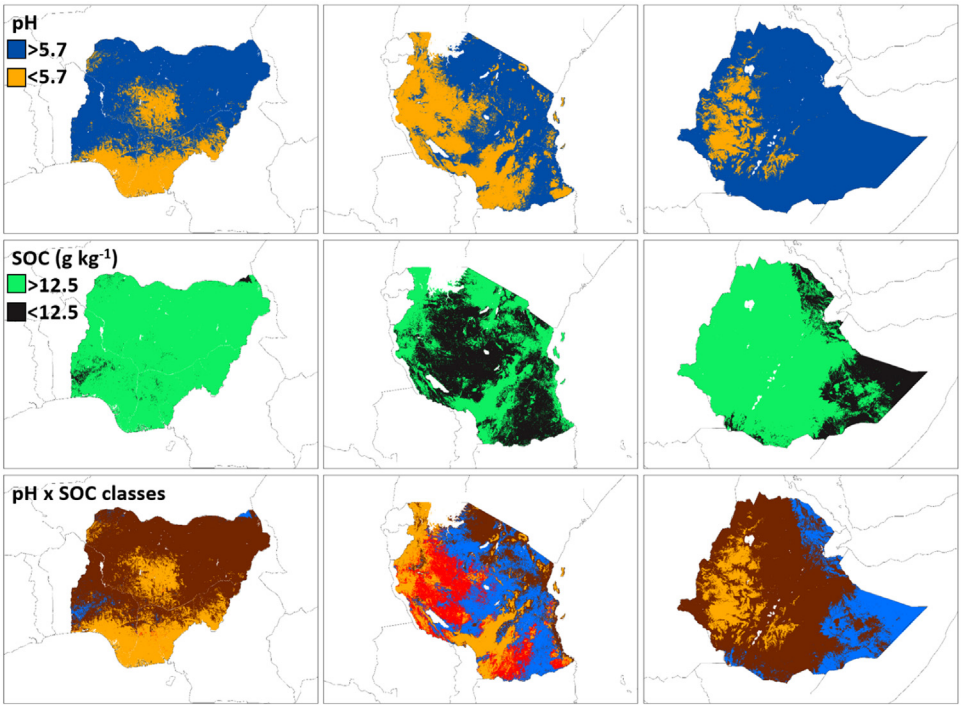

Fig. 3. Soil pH (top), soil organic carbon (SOC; middle), and soil classes (pH x SOC combinations; bottom) in the topsoil (0–30 cm) for Nigeria (left), Tanzania (center), and Ethiopia (right). Each color represents a pH x SOC combination in the bottom panels. Data source: http://www.isric.org. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

mapped to determine those that were predominant in each TED. However, these sub-domains were not considered spatially explicit for trial allocation given that local (field to field) variation may not be properly represented in the maps. While other soil variables may also influence crop response to fertilizer (*e.g.*, soil texture, CEC), we note that these variables are highly correlated with plant-available water holding capacity, pH, or SOC; hence, we did not include them in our analysis.

From a biophysical perspective, maize area and yield gap (as well as yield stability) are the most relevant variables to quantify potential impact of a given technology on maize production. However, high population density, better access to markets, and growing demand for livestock products are important drivers for farming system intensification in developing countries and, ultimately, determinants of technology adoption (Baltenweck et al., 2003; McIntire et al., 1992; Tesfaye et al., 2015). We note that this assumption may not apply in countries at a higher level of economic development with adequate infrastructure, mechanization, and access to markets. However, our assumption seems reasonable for a case study focused on SSA. Hence, for simplicity, we used cattle density, rural population, average distance to markets (as a measure of access to markets), and total maize area (Step 4, Fig. 1) as metrics to guide site selection and evaluate the potential impact associated with adoption of improved fertilization management practices aimed at increasing farmers net income. If other metrics such as income, farm size, child nutritional status were readily available within a complementary spatial framework, they too could be used in the evaluation. Gridded rainfed maize area in each country was retrieved from MAPSPAM (2005) (You et al., 2017; http://www.mapspam.info; Fig. 4), which represents the best current available source of area in SSA by crop type. Gridded data for rural population, cattle density, and distance to markets (travel time to nearest settlement with population > 20,000) were obtained from the Harvest Choice database (http://harvestchoice.org; Fig. 4).

We explored three scenarios in which current trial location was modified by limiting the number of sites per sub-domain and/or reallocating some of the existing sites to maximize coverage of maize production area, rural population, cattle density, and distance to markets, which are important factors governing adoption of improved nutrient management (Sadras et al., 2016; van Dijk et al., 2017), (Fig. 4). Scenario #1 was based on current distribution of trials but used TEDs and associated sub-domains to determine the number of sites needed to account for variation in soil classes (*i.e.*, pH x SOC combinations) within each TED. For simplicity, we assumed here that a minimum number of three sites per sub-domain (*i.e.*, combination of TED x soil class) is needed for a reasonable estimation of average response to fertilizer and its variability. Hence, we first selected those TEDs that currently have at least one site, and then allocated three experimental sites per sub-domain (soil class) until covering minimum 90% of total maize area within each TED. Sub-domains that accounted for a small share of crop area within each TED (< 5%) were omitted. The objective of this scenario was to evaluate whether current trial number per TED was excessive or insufficient to represent soil classes.

In scenario #2, sites were selected based only on maize area, ignoring proxies for socio-economic factors. We selected TEDs, starting from the one with largest maize area, allocating three sites per sub-domain within that TED, and then continued doing this with other TEDs until reaching the same number of sites as in the current project (*i.e.* 496). Same criteria as for scenario #1 was used to select/exclude subdomains within TEDs.

In scenario #3, sites were selected based on both maize area *and* the other three factors governing technology adoption. Hence, TEDs were ranked according to maize area, cattle head density, rural population, and proximity to markets. Overall ranking of TEDs was obtained based upon the sum of ranks, from the lowest to the highest values for each parameter. For simplicity, we assumed all variables to have the same weight, recognizing that, in reality, some of the variables may be weighted more heavily (*e.g.*, access to market). We assigned trials into sub-domains following the same procedure as in scenario #2.

Regional and national maize area and rural population coverage (Step 6; Fig. 1) were assessed for the current site distribution and for each scenario, assuming that those two variables are indicators of potential to improve maize production and farm income. For each scenario, ROI was estimated as the ratio between maize area or rural population and the total number of trials or their associated cost (in USD). For this calculation, we used an average cost of USD 360 per trial, including field activities, supplies, and data processing, as estimated by

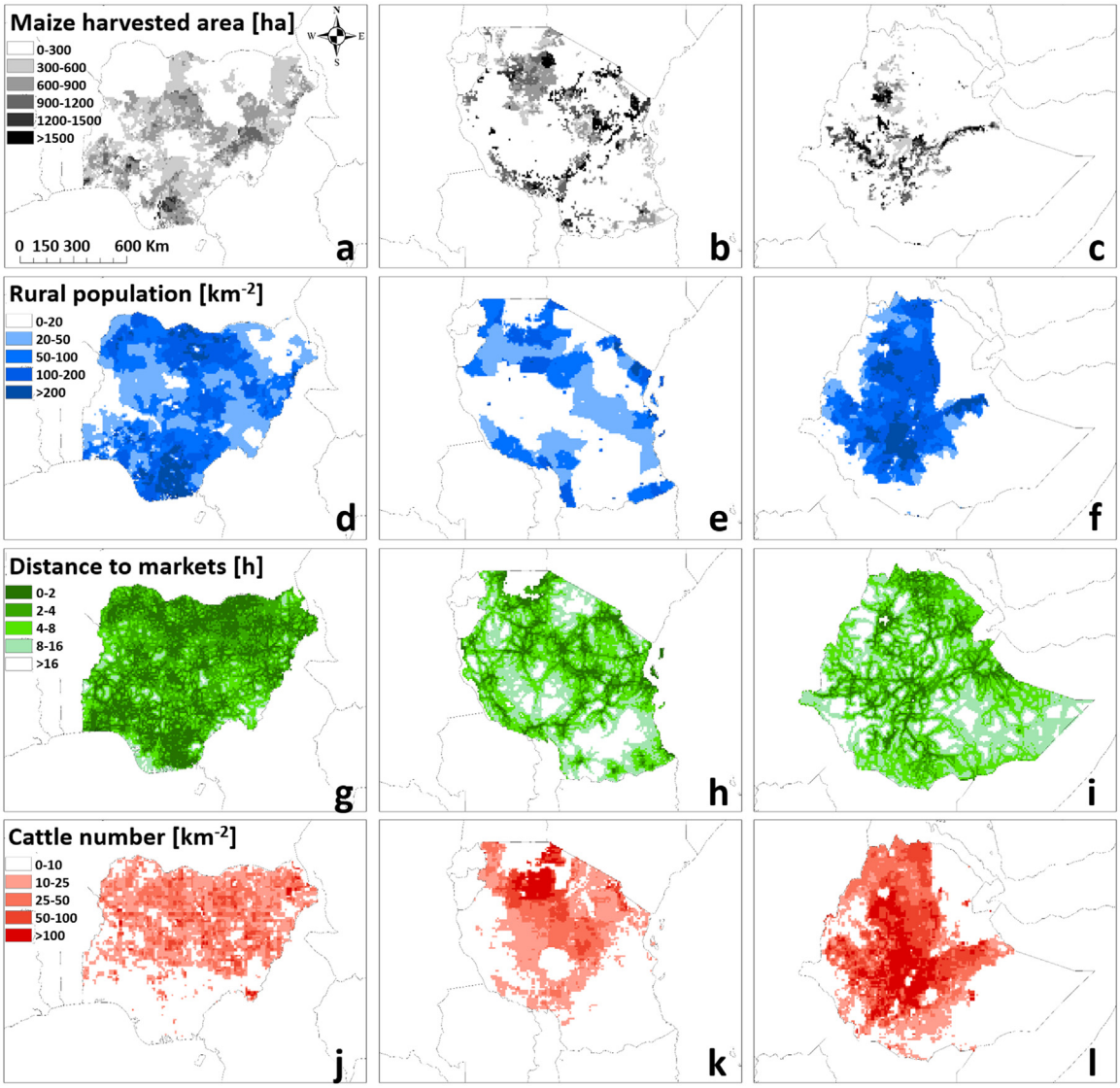

Fig. 4. Rainfed maize area (a, b, c), rural population (d, e, f), distance to market (g, h, i), and cattle number (j, k, l) in Nigeria (left), Tanzania (center), and Ethiopia (right). Some of these factors are co-linear and a correlation matrix table is provided in Table S1.

TAMASA researchers.

3. Results

3.1. Site location and ex-ante impact assessment

Fig. 5 shows the TEDs covered by the current experimental network and the three scenarios, while the number of sites per TED is shown in Table 1. Average maize area covered per trial by TAMASA was 5000, 5579, and 6780 ha in Ethiopia, Nigeria, and Tanzania, respectively (Table 1). The current trial network did not cover some important (top ranked) TEDs and, in some cases, there was only one experiment per TED (which would be too risky or insufficient to derive strong inferences) or, conversely, too many experiments (more than three per sub-domain, Supplementary Fig. S2). In the proposed scenarios (#1–3), this issue was addressed by assigning three sites per selected sub-domain, whereas in scenarios #2 and #3, some of the sites were also reallocated towards more important TEDs (Supplementary Fig. S2 g-l).

In scenario #1, the number of trials could be reduced by 20% in Ethiopia and still achieve the same maize area and rural population coverage as with the current site locations (Fig. 5, Supplementary Fig. S2 f, Table 1). Conversely, total number of sites would increase by 15% in Tanzania to meet the requirement of three sites per subdomain (Supplementary Fig. S2 e). In the case of Nigeria, there was little change in site number between the current trials and the improved scenario #1, although variability within each TED is better represented with the proposed scenario (Supplementary Fig. S2 d). Scenario #2 shows it would be possible to increase coverage of national maize area (79–134%) and rural population (14–33%) in Nigeria and Ethiopia, without increasing current number of sites, simply by reallocating some trials to other (unrepresented) TEDs with large maize area (Fig. 5, Supplementary Fig. S2 g-i, Table 1). For example, reallocation of some of the sites in Ethiopia following scenario #2 allowed representation of important maize producing areas in the eastern part of the country (Fig. 5). Conversely, little change was observed for Tanzania in terms of area coverage increase because major maize producing TEDs are covered by the current trials.

Site allocation based solely on maize area (scenario #2) changed little when socio-economic factors were taken into account for site selection in Nigeria and Tanzania (scenario #3). Indeed, 62% and 84% of selected TEDs in scenario #2 for Nigeria and Tanzania, respectively, were also selected following scenario #3 (Fig. 5 and Supplementary Fig. S2). The positive correlation between maize area and socio-economic related factors (especially rural population density and cattle density)

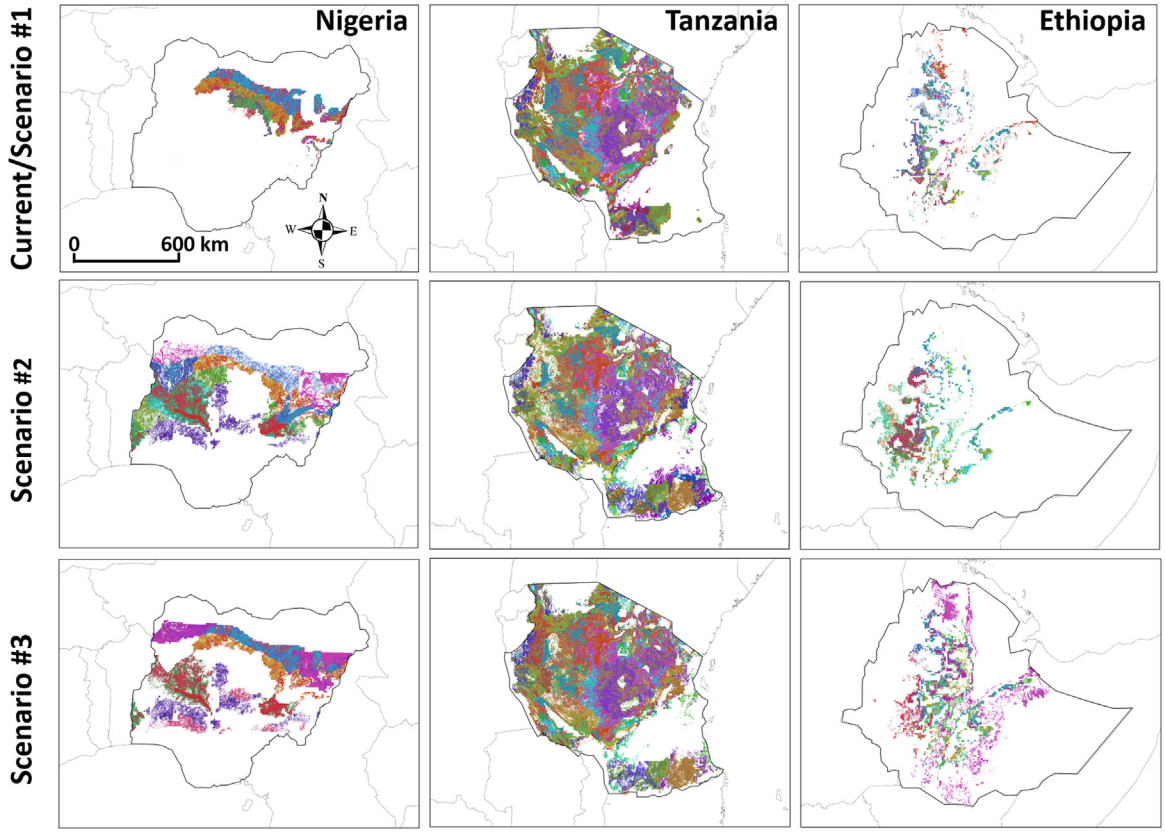

Fig. 5. Colored area represents technology extrapolation domains (TEDs) covered with current trial distribution and scenario #1 (upper), scenario #2 (center), and scenario #3 (bottom) in Nigeria (left), Tanzania (center), and Ethiopia (right). TEDs are based on both the climate zone scheme developed by van Wart et al. (2013) and spatial data on plant-available soil water holding capacity in the root zone from the Africa Soil Information Service (Leenaars et al., 2018; AfSIS). Each color corresponds to one TED. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

explained this finding (Fig. 6, Supplementary Fig. S1). Maize is the major staple food crop in all three countries and it was not surprising to find such strong correlation. However, selection of TEDs changed more between scenarios #2 and #3 in Ethiopia (only 50% of selected TEDs in scenario #2 were also selected in scenario #3) because some maize producing TEDs in the eastern region were selected at expense of others in the western region due to more favorable socio-economic context (Fig. 5). This is consistent with the greater data dispersion around the regression line observed for the ranking comparison in Ethiopia (Fig. 6).

Changes between current trial location and the three scenarios in terms of rural population coverage were similar to those reported for maize area (Table 1). An exception was the observed change between scenarios #2 and #3 for Nigeria and Ethiopia; in those cases, there was a substantial improvement in rural population coverage despite crop area coverage changing little as a result of selecting TEDs with relatively less maize area but higher population density. Considering crop area coverage and cost per trial for the three countries, current site location has a ROI of 17 ha per USD, with the alternative scenarios #2 and #3 increasing the ROI up to 22–24 ha per USD. Similarly, in terms of rural population, current site location reached 279 habitants per dollar invested. In this case, scenario #3 presented the highest ROI with 370 habitants per USD, while ROI for scenario #2 was 322 habitants per USD (Table 1).

Site reallocation led to an increase in maize area coverage from 5000 (Ethiopia), 5579 (Nigeria), and 6780 ha (Tanzania) per trial in the current network to respectively 8269, 12188, and 7222 ha per trial on average for scenarios #2 and #3 (Table 1; Supplementary Fig. 3). Changes in ROI in Nigeria and Ethiopia due to site re-allocation was substantial because of absence of trials in some important maize producing TEDs in the current site allocation (Supplementary Fig. S2).

Table 1
Changes in maize area and rural population coverage for the current site locations (C) and scenarios #1 (S1), #2 (S2), and #3 (S3) in Nigeria, Tanzania, and Ethiopia. Return on investment is presented as maize area or population coverage per USD. See also Supplementary Fig. 3.

	Nigeria				Tanzania				Ethiopia			
	C	S1	S2	S3	C	S1	S2	S3	C	S1	S2	S3
Number of trials	95	96	96	96	323	372	324	324	78	63	78	78
Maize area												
Total coverage (M ha)	0.53	0.53	1.25	1.09	2.19	2.19	2.39	2.29	0.39	0.39	0.70	0.59
Coverage per trial (ha ×1000)	5.5	5.5	13.0	11.3	6.8	5.9	7.4	7.1	5.0	6.2	9.0	7.6
Coverage per USD (ha)	15	15	36	32	19	16	20	20	14	17	25	21
Rural population												
Total coverage (M)	12.6	12.6	16.7	19.9	22.1	22.1	23.5	23.4	15.2	15.2	17.3	22.8
Coverage per trial (×1000)	132	131	174	207	68.4	59.4	72.5	72.2	195	241	222	292
Coverage per USD	368	365	483	576	190	165	201	201	541	670	616	812

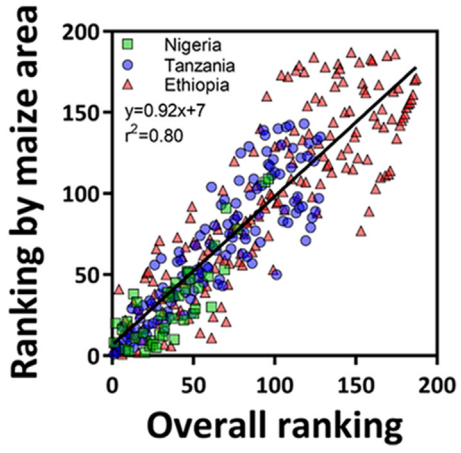

Fig. 6. Ranking of technology extrapolation domains (TEDs) based on maize area versus overall TED ranking based on both maize area and proxies for socio-economic factors (rural population, cattle density, and proximity to markets).

Rural population coverage per trial exhibited similar changes to those reported for maize area (Table 1; Supplementary Fig. 3). Conversely, site reallocation in Tanzania resulted in a relatively small increase in maize area and rural population coverage per trial because most important maize producing TEDs are currently covered, accounting for 75% of national maize area. Hence, limiting experimental sites to most relevant TEDs in Tanzania may be a much more convenient approach to increase ROI.

4. Discussion

The spectacular increase in crop production during the Green Revolution was driven by massive adoption of technological packages (high-yielding varieties, irrigation, fertilizer, pesticides) that were effective and predictable at increasing farmer yield and profit across a wide range of environments (Borlaug, 2007; Evans, 1997). Adoption of these technologies was facilitated by socio-economic factors such as better access to markets, subsidies for inputs, extensive capacity development, and mechanisms to support grain prices (Pingali, 2012). While highly successful at increasing crop production, the Green Revolution also led to inefficient use of inputs and associated negative environmental footprint (Pingali, 2012; Tilman et al., 2002). Perhaps more importantly, finding technologies with consistent impact on yield and yield stability across environments has become increasingly difficult, and governments and societies are now more reluctant to support policies (*e.g.*, subsidies) that facilitate farmer adoption of technologies (Myers and Kent, 2001). We argue that further increases in crop yields and input-use efficiencies will require better targeting of improved technologies to those geographic areas where these technologies are likely to be adopted and to have the greatest impact. The framework presented here provides a first step to improve current approaches to better target and scale out technologies and evaluate their potential impact.

Better impact assessment, based on extrapolation domains (TEDs) and other biophysical and socio-economic factors, represents an opportunity to improve representativeness and potentially therefore ROI in AR&D programs as shown for the maize program in SSA in this study. One of the strengths of this framework is to be able to integrate both biophysical and socio-economic variables for guiding site selection and *ex-ante* impact assessment. In our case study, we proposed an overall ranking to integrate biophysical and socio-economic factors in order to orient site selection towards TEDs with large maize areas and/or rural population coverage and where socio-economic context favors technology adoption. In practice, there will be a compromise between within-domain replication and the number of domains, especially where, for example, field to field (or even within-field) variation is known to be large (Tittonell et al., 2007, 2013). In the case of soil fertility, it is clear that even with > 20 trial sites in a 10 × 10 km pixel the range of responses cannot be easily captured (Kihara et al., 2016; Njoroge, 2017). In addition, experience with large numbers of spatially distributed trials in TAMASA shows that considerable replication is needed to account for unforeseen loss of trials, especially in more remote locations. Lastly, in the context of using frameworks for scaling out of technologies or innovations, the institutional context, *i.e.* the area of interest of the partner organization(s) doing the scaling, will be important and incorporating these institutions into the framework decision-making process is a key step. The who and the how, and not just the what and the where, are also important. Nonetheless, the framework is flexible enough so that the range of variables to be considered (and their weights) for impact assessment can be accommodated to the wide range of goals observed across AR&D programs.

Our analysis has focused on increasing representativeness, and potentially ROI, through fine-tuning of site selection at a national level, treating countries separately due to contrasting biophysical and socio-economic conditions. However, ROI can further increase if local results are extrapolated beyond national borders for countries sharing some TEDs (Omamo et al., 2006; Rattalino Edreira et al., 2018). In other words, the current trial design could be even more efficient by avoiding selection of the same sub-domains within TEDs in more than one country. For example, in scenario #3, it would be possible to reduce the total number of sites from 496 to 469 by avoiding allocation of sites into the same sub-domains across countries.

Similarity in selected TEDs with and without considering socio-economic factors was not surprising as it seems that regions with high maize area also exhibited high population and cattle density, though not closer proximity to markets. However, this finding cannot be generalized as we noted that the ranks used for TED selection may change depending upon the criteria used to weigh the socio-economic variables. For example, weighting distance to market more heavily than population and cattle density would have led to more contrasting results due to the weaker correlation between maize area and market proximity compared with correlations among maize area and rural population and cattle density (average r^2: 0.03 *versus* 0.63; Fig. S1). Likewise, socio-economic conditions are country-specific and the correlation among them, and with crop area, can change drastically between countries, especially between developed and developing countries. For example, maize area and population density are closely related in SSA but this association becomes very weak in developed countries as it is illustrated for USA in Fig. 7.

In our case study, for simplicity, we used maize area as a proxy to estimate potential impact on crop production. However, the current yield gap could also be used as a proxy in each TED, together with the expected degree of yield gap closure due to adoption of a particular technology, for estimating extra potential crop production. Following this approach, we estimated an extra maize production potential of 2.6 Mt, in TEDs covered with trials, for scenario #3 in Ethiopia. For this calculation, we used the best available estimates of yield gaps for Ethiopia (www.yieldgap.org) and assumed that adoption of improved fertilization practices would increase actual yields to a level of 50% of water-limited yield potential (from ≈18% in 2010 as estimated by van Ittersum et al., 2016). In turn, estimates of extra production potential would provide a basis to estimate gains in farmer income and improved diets, which ultimately translate into changes in poverty and nutrition. Finally, if complemented with measurements of key variables over time (*e.g.*, actual yields, climate), the yield gap can also be used as an indicator of impact over time, allowing monitoring and *ex-post* assessment.

This framework has the potential to be applied by a wide range of users with different objectives. For example, it could be used by private seed companies seeking greatest crop area coverage when evaluating cultivars, or by fertilizer supply companies that want to focus on areas

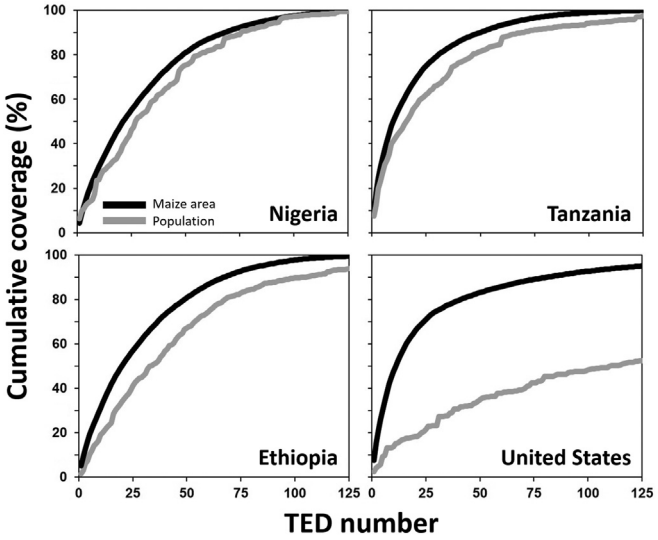

Fig. 7. Cumulative maize area (black line) and population (grey line) coverage. Technology extrapolation domains (TEDs) are sorted from highest to lowest maize area in each country. Data sources: http://sedac.ciesin.columbia.edu; http://mapspam.info.

with high return on farmer investment in increased use of nutrient inputs, while being close to markets and located within a large cropping area. From a different perspective, this framework could also be applied by governments, policy makers, or charitable foundations seeking to conduct agricultural research programs to reduce poverty/malnourishment or to identify areas with infrastructure limitations and large potential for food production (Gurara and Larson, 2013). To summarize, the framework is generic and flexible enough to accommodate the goals of a wide range of end users, being transparent regarding assumptions and data sources (and uncertainties). Hence, we believe that the framework has the potential to make a substantial contribution to improve investment and prioritization in AR&D, serving as a basis to estimate the impact on relevant variables such as food production increase and poverty and malnourishment reduction.

5. Conclusions

The spatial framework proposed here proved to be generic and robust when used for research site selection through maximizing the return on investment in AR&D programs in relation to explicit performance criteria. It acknowledges the importance of both biophysical and socio-economic related factors influencing technology adoption and impact, and gives flexibility to add more variables (biophysical, socio-economic, or both), with a defined weight, depending on user objectives. For these reasons, the proposed framework represents a significant step towards better *ex-ante* assessment of impact from AR&D programs that focus on food production, poverty reduction and/or hunger alleviation.

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Conflict of interest

The work described here has not been published previously and it is not under consideration for publication elsewhere. The publication is approved by all authors and tacitly or explicitly by the responsible authorities where the work was carried out. If accepted, the article will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright-holder.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.gfs.2018.12.006.

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